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Quantum Machine Learning Framework for Image Classification Using ResNet-Based Feature Extraction and QSVM

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Abstract- — Image classification has become a fundamental task in computer vision with applications in areas such as medical imaging, agriculture, environmental monitoring, and automated surveillance. Traditional machine learning techniques have achieved reasonable performance in classification tasks; however, they often struggle when dealing with high-dimensional and complex image datasets. Deep learning models, particularly Convolutional Neural Networks (CNNs), have significantly improved image classification performance by automatically learning hierarchical feature representations. Despite these advancements, classical deep learning models may still face challenges related to computational complexity and large-scale data processing.In recent years, quantum machine learning has emerged as a promising paradigm that combines principles of quantum computing with classical machine learning techniques to enhance computational efficiency and model performance. This study proposes a hybrid quantum–classical framework for image classification that integrates a deep residual network (ResNet-50) with a Quantum Support Vector Machine (QSVM). The ResNet-50 model is employed as a feature extraction mechanism to capture high-level visual representations from image data. The extracted features are then reduced in dimensionality using Principal Component Analysis (PCA) to simplify the feature space and improve computational efficiency.The reduced feature vectors are subsequently classified using a QSVM model that utilizes quantum feature maps to encode classical data into quantum states. Various quantum feature maps are explored to evaluate their impact on classification performance. Experimental results demonstrate that the hybrid quantum–classical approach achieves higher classification accuracy compared to conventional machine learning models such as Support Vector Machines and Random Forest classifiers. The proposed framework highlights the potential of combining classical deep learning architectures with quantum machine learning algorithms to address complex image classification challenges. This hybrid approach provides an efficient and scalable solution for advanced image analysis tasks and demonstrates the growing potential of quantum computing in artificial intelligence applications.

Index Terms:Quantum Machine Learning, Image Classification, Deep Learning, Residual Networks, Quantum Support Vector Machine, Hybrid Quantum-Classical Models, Feature Extraction, Principal Component Analysis.

I. INTRODUCTION

Image classification is one of the most important tasks in the field of computer vision and plays a significant role in many real-world applications such as medical diagnosis, agricultural monitoring, autonomous vehicles, and industrial automation. The objective of image classification is to automatically categorize images into predefined classes based on their visual content. Over the years, image classification techniques have evolved from traditional machine learning approaches to more advanced deep learning methods that can process complex image data more efficiently [10].

Traditional machine learning methods such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees, and Random Forest classifiers have been widely used for image classification tasks. These methods typically rely on manually extracted features obtained through image processing techniques such as edge detection, texture analysis, and histogram-based descriptors. Feature extraction methods such as Scale-Invariant Feature Transform (SIFT) and Histogram of Oriented Gradients (HOG) have also been applied to improve classification accuracy. However, these approaches often struggle when dealing with high-dimensional image data and complex feature representations [8].

With the advancement of artificial intelligence, deep learning models—particularly Convolutional Neural Networks (CNNs)—have revolutionized image classification. CNN architectures such as AlexNet, VGGNet, GoogLeNet, and ResNet have demonstrated remarkable performance by automatically learning hierarchical features directly from raw image data. For instance, the AlexNet architecture significantly improved image recognition performance on large-scale datasets such as ImageNet, marking a major milestone in deep learning research [4]. Similarly, the ResNet architecture introduced residual learning, enabling the training of very deep networks while mitigating problems such as vanishing gradients [5], [7].

Despite the success of deep learning models, they still face challenges related to computational complexity and high resource requirements, especially when processing large-scale image datasets. Training deep neural networks often requires significant computational power and memory resources, which may limit their scalability in certain applications [10], [11].

Recently, quantum computing has emerged as a promising technology capable of addressing complex computational problems that are difficult for classical computing systems. Quantum computing utilizes principles such as superposition, entanglement, and quantum parallelism to perform computations in fundamentally different ways from classical systems. These characteristics allow quantum algorithms to process certain types of problems more efficiently, opening new opportunities for machine learning applications [14].

Quantum Machine Learning (QML) is an emerging research field that combines quantum computing techniques with classical machine learning algorithms to improve model performance and computational efficiency. Several studies have explored the use of quantum algorithms for tasks such as optimization, classification, and pattern recognition. Quantum machine learning approaches have been applied in areas such as medical image analysis, cybersecurity, and data classification, demonstrating promising potential for solving complex data-driven problems [1], [16], [17].

In particular, Quantum Support Vector Machines (QSVMs) have shown promising potential in classification tasks by utilizing quantum kernels to represent complex data relationships in high-dimensional feature spaces. Quantum kernels allow classical data to be mapped into quantum feature spaces where complex patterns can be identified more efficiently [12], [13].

In this study, a hybrid quantum–classical image classification framework is proposed that integrates the strengths of deep learning and quantum machine learning. The proposed system utilizes a Residual Network (ResNet-50) model to extract meaningful features from image data, while a Quantum Support Vector Machine (QSVM) is employed for classification. Additionally, Principal Component Analysis (PCA) is applied to reduce the dimensionality of extracted features and improve computational efficiency [9].
The remainder of this paper is organized as follows. Section II presents a literature survey of related research in image classification and quantum machine learning. Section III describes the system analysis, including existing and proposed methods. Section IV illustrates the system architecture and methodology. Section V explains the system implementation and experimental setup. Section VI discusses the results and performance evaluation. Finally, Section VII concludes the paper and highlights possible directions for future research.

II. LITERATURE SURVEY

Image classification has been extensively studied in the fields of computer vision and artificial intelligence, with numerous approaches proposed to improve classification accuracy and computational efficiency. Over time, research has progressed from traditional machine learning techniques to advanced deep learning models and more recently to quantum machine learning frameworks. These developments aim to address the challenges associated with processing large-scale image datasets and extracting meaningful features from complex visual data [10].

Early image classification systems relied on classical machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, Naïve Bayes, Random Forest, and k-Nearest Neighbors (KNN). In these approaches, image data are first processed using feature extraction techniques such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT) to capture visual patterns within images. The extracted features are then used as inputs to classification models. Although these methods provide reasonable performance in certain applications, they often struggle with high-dimensional image data and complex feature representations [8].

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become the dominant approach for image classification tasks. CNN architectures such as AlexNet, VGGNet, GoogLeNet, and ResNet have demonstrated significant improvements in classification accuracy by automatically learning hierarchical features directly from raw image data. The AlexNet architecture marked a major breakthrough in image recognition by achieving state-of-the-art performance on the ImageNet dataset [4]. Similarly, the ResNet architecture introduced residual learning mechanisms that enable very deep neural networks to be trained efficiently while overcoming issues such as vanishing gradients [5], [7].

Recent studies have also explored the integration of quantum computing with machine learning, leading to the development of Quantum Machine Learning (QML) models. Quantum computing leverages principles such as superposition, entanglement, and quantum parallelism to process complex computations more efficiently than classical systems in certain scenarios. These capabilities have motivated researchers to investigate the use of quantum algorithms for classification, optimization, and pattern recognition tasks [1], [14].

One promising approach within quantum machine learning is the Quantum Support Vector Machine (QSVM). In QSVM models, classical data are mapped into quantum states using quantum feature maps, and quantum kernels are used to compute similarity between data points in high-dimensional quantum feature spaces. This approach allows the model to capture complex relationships within data that may be difficult for classical algorithms to represent [12], [13].

Several studies have proposed hybrid classical–quantum frameworks that combine the strengths of deep learning and quantum computing. In these architectures, classical deep learning models such as CNNs or ResNet are used for feature extraction, while quantum machine learning algorithms perform classification tasks. This hybrid approach allows deep learning models to effectively extract complex image features, while quantum models enhance classification performance through advanced kernel representations and optimization strategies [16], [18].

Despite these advancements, the practical implementation of quantum machine learning still faces several challenges. Current quantum hardware is limited by the number of available qubits, noise in quantum circuits, and limited scalability. These constraints restrict the execution of large-scale quantum algorithms and require hybrid quantum–classical approaches to effectively utilize quantum computing resources [2], [15].

Therefore, hybrid classical–quantum systems are considered a practical solution for leveraging the advantages of quantum computing while maintaining compatibility with existing classical computing infrastructures. Such systems combine the strong feature extraction capabilities of deep learning models with the advanced computational capabilities of quantum algorithms.

The proposed research builds upon these advancements by integrating ResNet-based feature extraction with Quantum Support Vector Machine classification. By combining deep learning with quantum machine learning techniques, the proposed system aims to improve image classification performance while demonstrating the potential of hybrid quantum–classical frameworks for solving complex image analysis problems.

III. SYSTEM ANALYSIS

A. Existing System

Traditional image classification systems primarily rely on classical machine learning algorithms and deep learning models to categorize images based on visual features. In these systems, images are first converted into numerical representations through feature extraction techniques such as Histogram of Oriented Gradients (HOG) and Scale-Invariant Feature Transform (SIFT). These extracted features are then used as input for classification algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Random Forest, Decision Trees, and Naïve Bayes. Although these techniques can perform well for certain applications, they often struggle to effectively process complex and high-dimensional image data.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) have become widely adopted for image classification tasks. CNN architectures such as AlexNet, VGGNet, GoogLeNet, and ResNet are capable of automatically learning hierarchical features from raw image data, eliminating the need for manual feature engineering. Among these architectures, ResNet (Residual Network) is particularly effective because it uses residual connections to overcome the vanishing gradient problem and enables the training of deeper neural networks. These models have significantly improved classification accuracy in many computer vision applications. Despite their success, classical deep learning models still face several challenges. Image datasets are often high-dimensional and require significant computational resources for training and inference. Additionally, deep learning models may struggle to efficiently process complex data patterns when the dataset becomes extremely large or highly nonlinear.

Recently, quantum machine learning (QML) has emerged as a promising alternative for solving complex computational problems. Quantum computing uses principles such as superposition, entanglement, and quantum parallelism, which allow quantum algorithms to process information more efficiently than classical algorithms in certain scenarios. Quantum machine learning models attempt to leverage these capabilities to improve classification performance and computational efficiency.

However, purely quantum machine learning systems are still limited by the current constraints of quantum hardware, including a limited number of qubits and noise in quantum circuits. As a result, hybrid approaches that combine classical deep learning with quantum machine learning are considered a practical solution for improving image classification performance.

Limitations Of Existing System

- Classical machine learning models rely heavily on manual feature extraction, which may not capture complex image patterns effectively.
- Deep learning models such as CNNs require high computational resources and long training times, especially when processing large datasets.
- High-dimensional image features increase computational complexity and model training cost.
- Many deep learning models operate as black-box systems, making their decision-making process difficult to interpret.
- Classical models may struggle to efficiently capture nonlinear relationships present in complex image datasets.
- Pure quantum machine learning models face hardware limitations, including limited qubits and noisy quantum circuits.
- These challenges highlight the need for a hybrid framework that combines classical deep learning with quantum machine learning techniques to improve classification performance.

B. Proposed System

To overcome the limitations of traditional image classification methods, this research proposes a hybrid quantum–classical machine learning framework that integrates deep learning with quantum computing techniques.

In the proposed system, image data are first collected from a dataset containing labeled images. The images then undergo preprocessing operations, including resizing and normalization, to ensure that they are compatible with the deep learning architecture used for feature extraction.

Next, ResNet-50 (Residual Network) is used to extract deep feature representations from the input images. ResNet-50 is a powerful deep learning architecture capable of learning complex hierarchical features while addressing the vanishing gradient problem through residual connections. The network outputs a high-dimensional feature vector representing the visual characteristics of each image.

Since the extracted features are high-dimensional, Principal Component Analysis (PCA) is applied to reduce the dimensionality of the feature space. PCA preserves the most significant information while reducing redundant features, improving computational efficiency and reducing the risk of overfitting.

After dimensionality reduction, the processed feature vectors are used for classification using Quantum Support Vector Machines (QSVM). QSVM extends the classical support vector machine by utilizing quantum kernels to map classical data into quantum states. This mapping allows the classifier to capture complex relationships in high-dimensional feature spaces more effectively.

Different quantum feature maps, such as Z feature map, ZZ feature map, and Pauli-X feature map, are used to encode classical feature vectors into quantum states. These feature maps transform classical data into quantum representations that can be processed by quantum circuits.

Finally, the performance of the proposed hybrid system is evaluated using standard classification metrics such as accuracy, precision, recall, and F1-score, along with stratified k-fold cross-validation to ensure reliable performance evaluation.

By combining deep learning feature extraction with quantum machine learning classification, the proposed framework improves image classification performance and demonstrates the potential of hybrid quantum–classical models for solving complex computer vision problems.

IV. SYSTEM DESIGN

System Architecture

Below diagram depicts the whole system architecture.

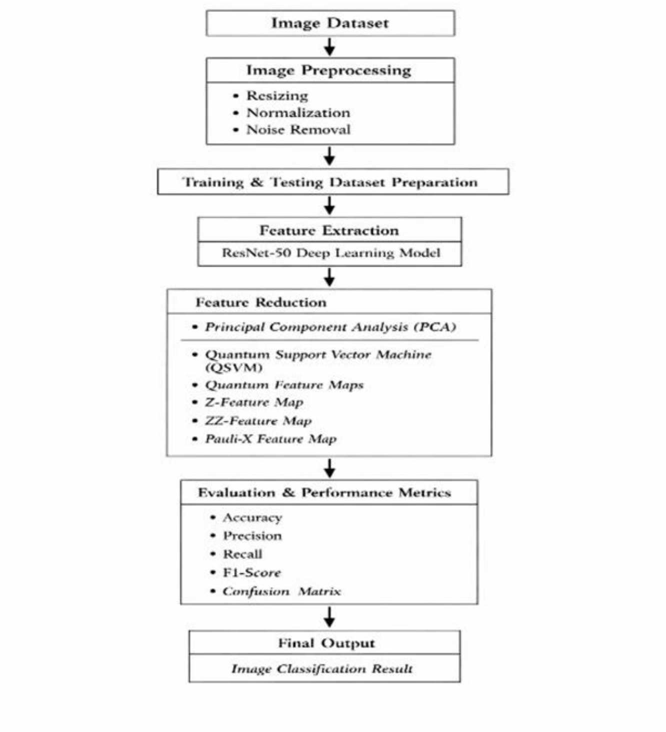

Fig. 1. Methodology followed for proposed model

V. SYSTEM IMPLEMENTATION

Modules

This section describes the implementation modules of the proposed hybrid quantum–classical image classification framework. The system follows a modular pipeline consisting of image data acquisition, preprocessing, feature extraction, dimensionality reduction, quantum classification, and prediction evaluation. This structured design improves system efficiency, scalability, and classification accuracy for complex image datasets.

A.Data Collection Module

The Data Collection Module is responsible for gathering image data used for training and testing the classification model. The dataset consists of labeled images belonging to different predefined categories. These images may be obtained from publicly available datasets or domain-specific image repositories used for computer vision research.The collected image dataset contains various visual patterns and features that represent different classes. Each image is stored in a structured format along with its corresponding label, enabling supervised learning for image classification. The collected images are forwarded to the preprocessing module for further processing.

B. Image Preprocessing Module

The Image Preprocessing Module prepares the dataset for feature extraction and model training. Image datasets often contain variations in image size, noise, illumination, and background information that can negatively affect model performance if not properly handled.

The preprocessing stage includes the following steps:

1) Image Resizing
All images are resized to a consistent resolution to ensure compatibility with the deep learning architecture used for feature extraction.

2) Noise Removal
Noise reduction techniques are applied to eliminate unwanted distortions and improve image quality.

3) Image Normalization
Pixel values are normalized to maintain a consistent range of values across the dataset. Normalization helps improve the stability and convergence of deep learning models.

These preprocessing steps ensure that the input images are properly formatted and suitable for further feature extraction.

C. Feature Extraction Module

The Feature Extraction Module uses a deep learning architecture to extract meaningful features from the preprocessed images. In the proposed system, ResNet-50 (Residual Network) is employed for this task.ResNet-50 is a deep Convolutional Neural Network that uses residual connections to enable efficient training of very deep networks while mitigating issues such as vanishing gradients. The network automatically learns hierarchical image features, including edges, textures, shapes, and complex visual patterns. The output of the ResNet model is a high-dimensional feature vector representing each image. These feature vectors contain important information that can be used for image classification.

D. Dimensionality Reduction Module

Since the extracted deep features are often high-dimensional, a Dimensionality Reduction Module is incorporated to reduce computational complexity.

In this module, Principal Component Analysis (PCA) is applied to transform the high-dimensional feature vectors into a lower-dimensional space while preserving the most significant

information. PCA reduces redundancy among features and improves computational efficiency during model training.
By reducing the dimensionality of feature vectors, this module helps prevent overfitting and accelerates the training process.

E. Quantum Classification Module
The Quantum Classification Module performs image classification using Quantum Support Vector Machines (QSVM). QSVM is a quantum machine learning algorithm that extends the classical Support Vector Machine by utilizing quantum kernels.

In this module, classical feature vectors are encoded into quantum states using quantum feature maps such as:

- Z Feature Map
- ZZ Feature Map
- Pauli-X Feature Map

These feature maps convert classical data into quantum representations that can be processed within quantum circuits. The QSVM algorithm then computes similarity between data points using quantum kernels, enabling the system to capture complex relationships within the dataset.

The use of quantum kernels allows the classifier to build more effective decision boundaries in high-dimensional feature spaces.

F. Prediction and Evaluation Module
The Prediction and Evaluation Module generates the final image classification results and evaluates model performance.
Once the QSVM model is trained, the system can classify new images by passing them through the same preprocessing, feature extraction, and dimensionality reduction pipeline. The trained QSVM then predicts the corresponding class label for each input image.

The output of the classification system includes:
- Predicted image class label
- Classification confidence score

To evaluate model performance, several evaluation metrics are used:
- Accuracy
- Precision
- Recall
- F1-Score

Cross-validation techniques are also applied to ensure reliable model performance and prevent overfitting.

By combining deep learning feature extraction with quantum machine learning classification, the proposed system improves image classification accuracy and demonstrates the effectiveness of hybrid quantum–classical machine learning frameworks in computer vision applications.

VI. RESULTS AND DISCUSSION

This section presents the experimental results and performance evaluation of the proposed hybrid classical–quantum image classification framework. The system integrates ResNet-50 for feature extraction and Quantum Support Vector Machine (QSVM) for classification. The experiments were implemented using Google Colab, utilizing TensorFlow Keras for deep learning and Qiskit for quantum machine learning components. The performance of the proposed model was evaluated using stratified 5-fold cross-validation, ensuring that each fold maintained the same class distribution for reliable evaluation. The classification task focused on distinguishing between healthy and diseased potato images. The results were compared with classical machine learning models such as Support Vector Machine (SVM) and Random Forest (RF).

A. Accuracy Comparison of Classical and Quantum Models
To evaluate the effectiveness of the proposed framework, several classification models were implemented and compared. These models include:

- Support Vector Machine (SVM)
- Random Forest (RF)
- Quantum Support Vector Machine (QSVM)

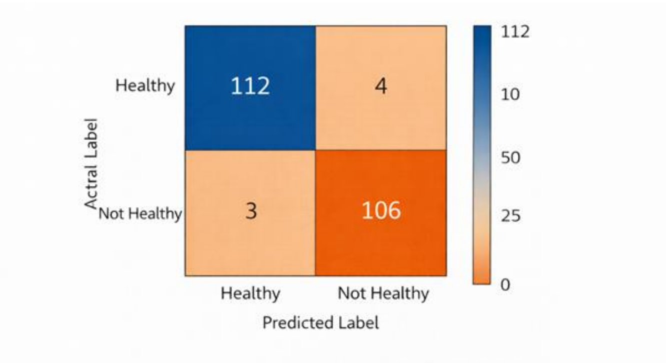

Fig. 2. Predicted vs Actual Image Classification Results

Dimensionality reduction was applied using Principal Component Analysis (PCA) with three configurations: 3, 6, and 9 components.

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Table 1
Performance Comparison of Classical and Quantum Models

PCA Components	SVM	Random Forest	QSVM (Z Feature Map)
3	0.5658	0.9689	**0.9923**
6	0.5658	0.9455	**0.9846**
9	0.5658	0.9766	**0.9923**

From the results, the Quantum Support Vector Machine with the Z-feature map achieved the highest classification accuracy of 99.23%, outperforming classical machine learning models such as SVM and Random Forest. This superior performance demonstrates the ability of quantum kernels to capture complex relationships within the feature space more effectively than classical algorithms.

B. Analysis of Quantum Feature Maps
In addition to classical model comparison, the study also evaluated the impact of different quantum feature maps used in the QSVM model. The tested feature maps include:

- ZZ Feature Map
- Z Feature Map
- Pauli-X Feature Map

Table 2Accuracy of QSVM with Different Feature Maps

PCA Components	ZZ Feature Map	Z Feature Map	Pauli-X Feature Map
3	0.9615	**0.9923**	0.5658
6	0.9154	**0.9846**	0.5658
9	0.6662	**0.9923**	0.5658

The results indicate that the Z feature map consistently achieved the highest classification accuracy across all PCA configurations. The ZZ feature map also demonstrated strong performance, while the Pauli-X feature map produced significantly lower accuracy.

The improved performance of the Z feature map can be attributed to its ability to encode classical data efficiently into quantum states while maintaining strong separability between classes in the quantum feature space.

C. Discussion of Results
The experimental results demonstrate the effectiveness of integrating classical deep learning with quantum machine learning techniques. The ResNet-50 model successfully extracted high-level features from image data, while PCA reduced the dimensionality of these features, improving computational efficiency.By incorporating Quantum Support Vector Machines, the proposed framework was able to achieve higher classification accuracy compared to classical machine learning models. The use of quantum kernels enabled the model to capture complex feature interactions that may be difficult for classical algorithms to detect.

Furthermore, the results confirm that feature map selection plays a crucial role in QSVM performance, with the Z feature map providing the best classification results in this study.

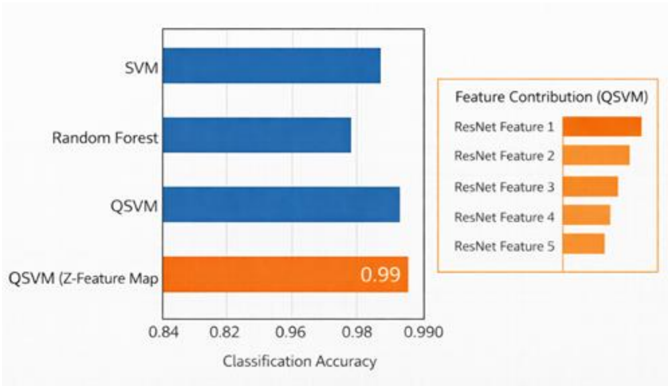

Fig. 3. Model Performance and Feature Contribution Analysis

Overall, the proposed hybrid ResNet-QSVM model demonstrates strong potential for improving image classification accuracy and highlights the benefits of integrating quantum computing techniques with classical deep learning frameworks.

VII. CONCLUSION AND FUTURE WORK

This study proposed a hybrid quantum–classical machine learning framework for image classification by integrating ResNet-50 feature extraction with Quantum Support Vector Machine (QSVM) classification. The proposed framework aims to address the limitations of traditional machine learning and deep learning approaches when handling high-dimensional image datasets.

In the proposed system, ResNet-50 was used to extract deep feature representations from image data, while Principal Component Analysis (PCA) was applied to reduce the dimensionality of the extracted features and improve computational efficiency. The reduced feature vectors were then used for classification using Quantum Support Vector Machines with different quantum feature maps, including Z-feature map, ZZ-feature map, and Pauli-X feature map. These techniques allow classical image features to be encoded into quantum states, enabling quantum kernels to capture complex relationships within the dataset [12], [13], [14].

Experimental results demonstrated that the QSVM model with the Z-feature map achieved the highest classification accuracy of approximately 99.23%, outperforming classical machine learning models such as Support Vector Machine (SVM) and Random Forest. These findings highlight the effectiveness of integrating deep learning feature extraction with quantum machine learning techniques for complex image classification tasks [1], [2], [16].

The proposed hybrid framework demonstrates the potential advantages of combining classical deep learning models with quantum machine learning algorithms to enhance predictive performance while efficiently processing high-dimensional data. Such hybrid approaches represent an emerging direction in artificial intelligence research and may significantly improve the performance of future image classification systems [15], [17].

Future work may focus on implementing the proposed model on real quantum computing hardware instead of simulators to evaluate its practical performance in real quantum environments. Additionally, exploring advanced quantum feature maps, quantum neural networks, and hybrid quantum–classical ensemble models may further improve classification accuracy and model robustness. Expanding the framework to larger and more diverse image datasets may also enhance the scalability and real-world applicability of the proposed system [18], [19].

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